Examining Short-Selling and Stock Returns without Negative Short-Selling Data

Youngsoo Bae[*] Kyeong-Hoon Kang[†]

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Abstract

Since buying is the opposition transaction of not only short-selling but also (simple) selling, aggregate stock purchase data cannot be used as negative short-selling. Given that we cannot observe negative short-selling data, empirical studies on short selling without consideration of this critical point could produce erroneous results. Based on econometric models that incorporate deficiency of negative short sales data, we examine the relationships between short selling of Korean stocks and their returns. We find the inclusion of the non-negativity of short-selling data leads to significantly different estimation results. Firstly, in the regression of short sale ratios on past returns, Tobit models produce statistically significant positive coe icient estimates, while linear models produce only statistically insignificant negative coe icient estimates. Secondly, in the regression of future returns on short sale ratios, we find a smaller negative coe icient estimate with a dummy variable than without a dummy variable. Since it is evident that we cannot gather negative short-selling data, these differences indicate that changes are necessary in the estimations on short-selling and stock returns.

1 Introduction

This paper raises a question regarding the econometric methodology of empirical studies on short-selling and stock returns. Short selling describes the process of selling borrowed stocks to buy the same instruments later at a cheaper price to pay back the borrowed stock, making profits from the exchanges. It is a bet on the forecast that the targeted shares would perform poorly in the future.

When short-sellers do not expect a decline in the stock price, however, they do not sell the stocks short. For example, if they expect the stock price will rise, they might buy and own its shares and they are in long positions. For instance, an investor who owns 100 shares of Apple stock in their portfolio is said to be long 100 shares. If the investor has short positions, on the contrary, the investor owes those stocks to someone, but does not actually own them yet. Continuing the example, an investor who has sold 100 shares of

[*]School of Economics, University of Seoul, ✉ysbae@uos.ac.kr
[†]College of Business Administration, Dongguk University, ✉khkang@dongguk.edu

Apple without yet owning those shares is said to be short 100 shares. The short investor owes 100 shares at settlement and must fulfill the obligation by purchasing the shares in the market to deliver.

As in these instances, buying or long position is the opposition transaction of short-selling or short-position. It is noticeable, however, that aggregate stock purchase data cannot be used as negative short-selling. It is because buying is the opposition transaction of not only short-selling but also (simple) selling. Investors buy stocks for many reasons: to make capital gains, to receive regular dividends, to defend against hostile M&A pressure, or to take control of a target firm and so on, and we do not know how much of it is the opposition of short-selling or simple selling.[1]

At this point, we argue that there are two kinds of zero short-selling. If a short seller is not sure about the future movement of a stock price or expects that the stock price will change very little, she will neither sell the stocks short nor buy them. Even in this situation, there could be transactions of the stock: some sellers need liquidity and some other investors sell their shares not expecting capital gains in the near future. On the other hand, when the short seller expects a substantial rise in the price of the stock, she does not sell the stocks short but buy them.[2] This transaction, buying stocks, is different from no short-selling without buying, but most empirical papers on short-selling do not distinguish, at least explicitly, these two different "zero short-selling."

Empirical studies on short selling without consideration of this critical point could produce consistently inaccurate and sometimes erroneous results. In most of the empirical studies examining whether short sellers are making their decisions based on short-term overvaluation, linear regression models have typically been used without considering that there are two different kinds of zero short-selling. The resulting regression line may underestimate the true slope coefficient. In the meantime, regressions for short sellers' returns predictability can lead to overestimation of the slope coefficient if they do not include the non-negativity of short sales. We do a related experiment using pseudo data and find the under- and over-estimation problems.[3]

Based on econometric models that incorporate the two different kinds of zero short-selling, we examine the relationships between short-selling and stock returns. We provide test results to both the empirical questions as in Diether, Lee, and Werner (2009): what effects short sales make on future returns, and how short sellers react to past returns. For the empirical test, we use daily short sale and stock return data of 215 Korean firms that are listed in the Korea Composite Stock Price Index (KOSPI) from Jan. 2nd, 2006 to Sep. 30th, 2008.

We find the inclusion of the non-negativity of short sales leads to significant differences

[1]The difference between selling and short-selling explains why there are so many research papers on short-selling and short-sellers.

[2]In fact, many typical short-sellers buy stocks. For example, hedge funds are known to employ a long/short equity strategy. It is an investing strategy of taking long positions in stocks that are expected to appreciate and short positions in stocks that are expected to decline. According to market commentators, many hedge funds use the strategy with a long bias (such as 130/30, where long exposure is 130% and short exposure is 30%).

[3]The third section about our econometric models reports the results.

in the estimation results. Firstly, in the regression of short sale ratios on past returns, Tobit models produce statistically significant positive coefficient estimates, while linear models produce only statistically insignificant negative coefficient estimates. Secondly, in the regression of future returns on short sale ratios, we find a smaller negative coefficient estimate with a dummy variable than without a dummy variable. As stated above, it is evident that we cannot observe negative short sales data. If we agree on this point, the differences in the test results between the previous studies and ours can indicate the necessity that the econometric methodology should be modified. The bigger the differences are, the more necessary the modification of the regression model is.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Problems in the econometric models of previous research are discussed and our econometric models are presented in Section 3. Section 4 reports the estimation results and Section 5 suggests some conclusions.

2 Related Literature

Although there is extensive literature about short sales that has been carried out over many years, most explore the impact of short sale constraint on security prices. Miller (1977), Jarrow (1980), Feglewski (1981), Danielsen and Sorescu (2001), Chen, Hong, and Stein (2002), Jones and Lamount (2002), Ofek and Richardson (2003), Boehme, Danielsen, and Sorescu (2006), Chang, Cheng, and Yu (2007), Bris, Goetzmann, and Zhu (2007), and Saffi and Sigurdson (2011) find that short sales constraint causes stock prices to be upward biased and that the overvaluation tends to decline after the constraint relaxation. The relationship between short sales restrictions and stock price has recently been reinvestigated in many ways because many countries tightened their regulations to restrict short selling during the 2008 global financial crisis. Boehmer, Jones, and Zhang(2009), Boulton and Braga-Alvis(2010), Kolasinksi, Reed, and Thornock(2010), and Autore, Billingsley, and Kovacs(2011) document that short sales restrictions cause overpricing of stocks, deteriorate market quality and liquidity, and undermine price efficiency.

It is relatively conventional to examine the relationship between short selling and stock returns. Accessibility of data on actual short selling transactions, however, shed new light on this study. Prior studies cannot but use monthly short interest data for individual stocks because exchanges in the US stock market publicly disclose the aggregate level of short positions in their listed stocks for a single day, around the middle of each month. Therefore, researchers can observe only the change in the monthly short positions and have limitation to reveal the exact price movement surrounding actual short selling transactions.

Angel, Christophe, and Ferri (2003) is the first study that uses transaction data consisting of short trades reported to Nasdaq through its ACT trade-reporting system and Boehmer, Jones, and Zhang (2008) employ a long panel of executed short sale orders submitted electronically to NYSE from 2000 to 2004. The comprehensive study with daily short selling data conducted by Diether et al. (2009) covers all short selling carried out in the US market including NYSE, AMEX, local exchanges, and Nasdaq. Engelberg, Reed and Ringgenberg (2010) extract information on short sales transactions from the NYSE TAQ Regulation SHO database. SEC adopted the Regulation SHO in 2005 to establish 'locate' and 'close-out' standards to prevent the unethical short sale trade. Earlier than all of these studies, Aitken, Frino, McCorry, and Swan (1998) apply short sales on an intraday basis in Australia, where the Australian Stock Exchange (ASX) immediately disclose short sale transactions to the public.

The empirical results of the expected relationship between short selling (interest) and stock returns are mixed depending on whether short sellers are considered to be informed traders or uninformed ones. Short sales are unrelated or even positively related to subsequent abnormal returns of stocks under the assumption of uninformed traders, while they are negatively linked to stock returns under the assumption of informed traders.

Brent, Morse, and Stice (1990) find that monthly short interest does not predict either cross-section or time-series stock returns, and indicate that short selling takes place for arbitrage reasons. Figlewski and Webb (1993) provide indirect evidence that short trades are less likely to be informative because short selling activity is generally greater for optioned stocks whose put price increase and call price decrease reflecting the use of options by traders with unfavorable information. Woolridge and Dickinson (1994) indicate a positive but statistically insignificant relation between changes in short position and stock prices. Lamont and Stein (2004) find that aggregate short interest both during the dot-com era and at other times react to past price movement, but do not have predictability for future price movement. These results are likely due to the use of once-per-month short interest data or the use of restrictive small samples. In practice, short interest can be even interpreted to be a bullish signal because the shares will be eventually purchased to cover the short position.[4]

The notion that short sellers are informed traders is advanced by Diamond and Verrechia (1987) who develop a theoretical model in which short selling is, because of costly constraint, the domain of informed traders. Consequently, an increase in the amount of short interest is a bad signal associated with negative stock returns. Asquith and Meulbroek (1996) investigate whether firms that are heavily shorted subsequently experience negative returns and detect a strong negative relation between short interest and subsequent returns. Aitken et al. (1998) find that stock prices following short sales in Australia decreases up to -0.20 percent with adverse information made public within fifteen minutes or twenty trades. Ackert and Athanassakos (2005) also find that short sales and excess returns are contemporaneously negatively correlated in Canada. Desai, Ramesh, Thiagarajan, and Balachandran (2002) detect that heavily shorted firms in Nasdaq experience significant negative returns after controlling market, size, book-to-market ratio, and momentum factors, indicating that a higher level of short interest is a stronger bearish signal. Asquith, Pathak, and Ritter (2005) recognize the competing effects of short interest (shorting supply) and institutional ownership (shorting demand) and find that stocks with high shorting demand and low shorting supply are more likely to underperform due to the binding of short sale constraints. Cohen, Diether, Malloy

[4] McDonald and Baron (1973) find that short sellers earn negative returns and are not able to generate excess returns of naive short selling portfolio activity.

(2007) employ an identification strategy that allows us to isolate shifts in the supply and demand for shorting, and show that increases in shorting demand have significantly negative effects on future stock returns. They also suggest that the shorting market is a mechanism for private information revelation because predictable increases in shorting demand which are not related to private information do not influence future returns. Boehmer et al. (2008) find that heavily shorted stocks underperform lightly shorted stocks by a risk-adjusted average of 1.16% over the following 20 trading days and that institutional nonprogram short sales are the most informative.

Diether et al. (2009) investigate the relationship between short selling and antecedent stock returns as well as subsequent stock returns. In other words, it is examined how short sales relate to not only future returns but also to past returns. They find that short sale activity is strongly positively related to past returns, but that an increase in short selling is associated with a future decline in stock returns. Angel et al. (2003) also explore short selling on the Nasdaq and observe that short selling is more common among stocks with high returns than stocks with weaker performance.

In terms of methodology, no one has previously examined the relationship between short selling and stock returns with the notion that short sales cannot be negative. Most studies use a linear model to regress stock returns on short selling (ratio) at prior periods. They pay attention to time lag at most between two variables in pooled, cross-sectional, time series, or panel regression. Of course, some other dependent variables are added to clarify what researchers try to figure out in the study. Stock returns are usually adjusted by using the Fama and French (1993) three factor or the Carhart (1997) four factor model. For example, Boehmer et al. (2008) use market capitalization, book to market ratio, return volatility, turnover ratio, and short selling order in balance as independent variables, and Cohen et al. (2007) employ dummy variables representing inward demand shift, outward demand shift, inward supply shift, outward supply shift, institutional ownership, loan fee as explanatory variables. Diether et al. (2009) regress daily shorting activity on past returns, effective spread, and buy order imbalance on individual stock level to investigate short selling reaction to past returns, and use three- and four-factor model regressions for short selling activity portfolios to examine whether short sellers predict future returns. Other researchers concerned with short interest apply more simple methodology. They classify stocks depending on short interest level, regress excess individual stock returns on three or four factors, and interpret the relationship of the short sales and stock returns. Consequently, we believe our study is the first to look at the non-negative feature of short selling, which is overlooked in existing literature.

3 Econometric Model

In this paper, we examine the following two questions about the relationship between short selling and stock returns:

1. Whether short sellers are making their decisions based on short-term overvaluation.

2. Whether short sellers are successful in predicting future stock returns.

If short sellers are reacting to short-term overvaluation, short selling activity should increase after higher stock returns. And, if short sellers are to be claimed as successful investors, stock returns should be lower after higher short selling activity.

To empirically investigate these two questions, we propose a Tobit model and a model with a dummy variable, which can incorporate the non-negativity of short sales explicitly.

For the first question of whether past stock returns have a positive impact on short selling activity, we propose the following Tobit model:

$$s_{it} = \begin{cases} s_{it} & \text{if } s^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$s^*_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it} \tag{2}$$

where s_{it} is short sale ratio, which is defined as short sale transaction divided by total transaction, $r_{it-1,-5} = p_{it-1} - p_{it-6}$ where p_{it} is the logarithm of stock price, and s^*_{it} is the latent variable for s_{it}. Equation (1) and (2) can be written more compactly as

$$s_{it} = \max(\alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}, 0).$$

We choose 5-day stock returns because most short selling transactions are in the short-term and it is also used by Diether et. al. (2009). To check the robustness of our estimation results, we conduct every analysis in this paper with different lengths of past stock returns from 1 to 5. Results are largely similar; therefore, in this paper we only present and discuss results with 5-day stock returns.

In previous literature, typically the following linear regression model has been used,

$$s_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}.$$

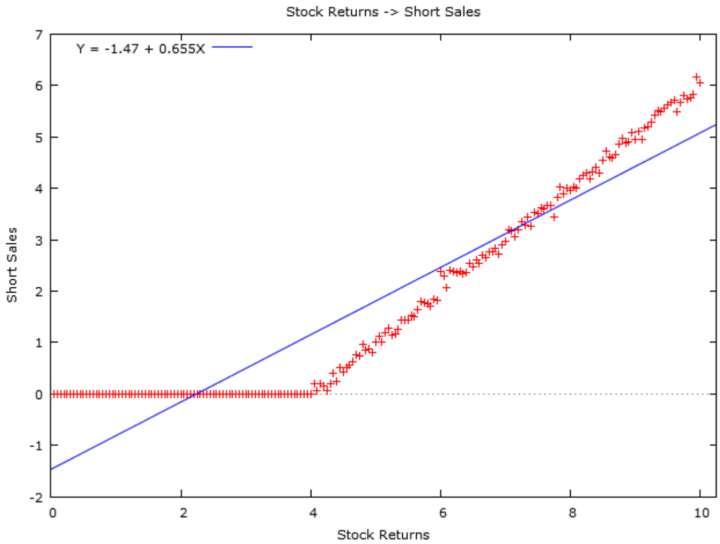
For example, see Diether et. al. (2009). However, since short sales cannot be negative, the linear model does not estimate the coefficients consistently. To emphasize this point, we generate pseudo data by the following truncated equation,

$$y_t = \max(-4 + x_t + e_t, 0),$$

and estimate it by using the linear regression model, which is a kind of mis-specification. The estimated regression equation and generated data are shown in Figure 1. From this figure, we can see clearly that the linear regression method cannot produce a consistent estimate of the true slope coefficient. Therefore, it is reasonable to conjecture that we will find a larger slope coefficient estimate from the regression of short sales on past stock returns, if we use a Tobit model, which is a correct model.

For the second question of whether short sellers are successful in predicting future lower

Figure 1: Difference between Tobit Model and Linear Regression Model



stock returns, we propose the following linear regression model with a dummy variable,

$$r_{it,5} = \beta_0 + \beta_1 s_{it} + \gamma d_{it} + u_{it}$$

where $r_{it,5} = p_{it+5} - p_{it}$, which is 5-day future stock returns[5], and d_{it} is a dummy variable that is set to 1 if $s_{it} = 0$ and 0 otherwise. As for the first question, we illustrate the difference between a model with a dummy variable and without a dummy variable in Figure 2. It is clear that the slope coefficient is overestimated without a dummy variable. Therefore, we can conjecture that if we include a dummy variable, an impact of short sales on future stock returns will be smaller.

4 Estimation Results

4.1 Data

We use daily short sales and stock returns data of 215 Korean private firms that are listed on the Stock Market Division of the Korea Exchange, previously known as the Korean Stock Exchange. They are all included into the Korea Composite Stock Price Index(KOSPI), which is a representative stock market index of Korea, like the Dow Jones Industrial Average or S&P 500 in the U.S. Our data set begins on January 2nd, 2006 and ends on September 30th, 2008. The reason that the data span ends on September 30th, 20008 is because short selling was banned by the Korean government due to the global financial crisis.

Summary statistics of the two main variables, short sale ratios and 5-day stock returns, are given in Table 1. Out of a total of 144,315 valid observations (stocks×days), 50.8% of

[5]For the same reason in the previous section, we choose 5-day future stock returns. Results are robust with different lengths of future stock returns from 1 to 5.

Figure 2: Difference between with Dummy and without Dummy

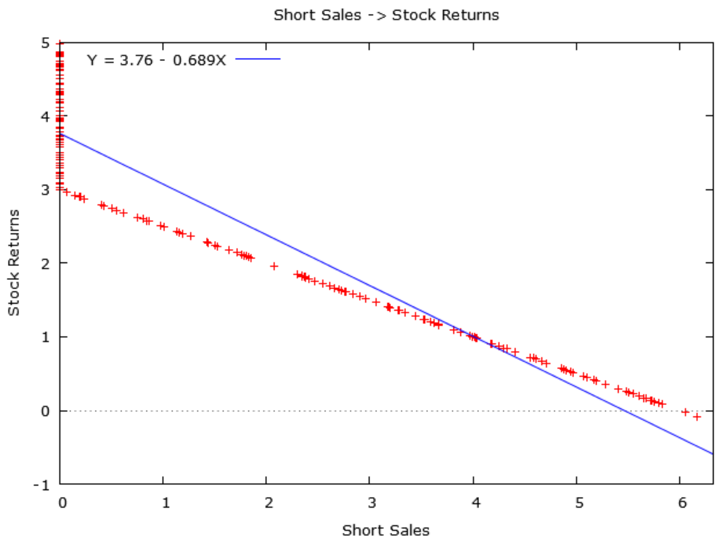


Table 1: Summary Statistics of Short Sale Ratios and 5-day Returns

	N	Min	Median	Max	Mean	SD
Short sale ratio	144,315	0.00	0.00	0.81	0.01	0.04
Short sale ratio > 0	70,972	0.0000006	0.0096	0.81	0.029	0.0499
5-day return	144,315	-1.18	0.00	0.68	0.00	0.07

them have no short sale transactions. This indicates that the non-negativity of short sales cannot be just ignored.

To have a better idea of the distribution of short sale ratios and 5-day stock returns, we draw their histograms. Figure 3 is the histogram of short sale ratios and the histogram of 5-day stock returns. It is clear that short sales cannot be negative, and most observations have simply zero short sale ratios.

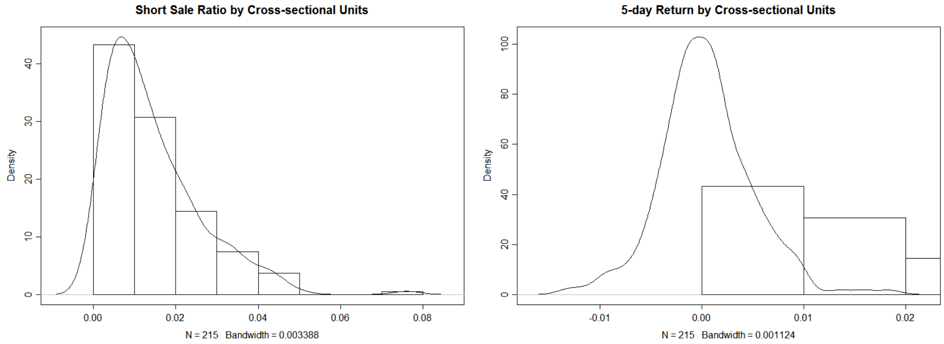
4.2 Impact of Stock Returns on Short Sales

In this subsection, we investigate the impact of past stock returns on short selling activity. Since previous literature mostly use a linear regression model, in addition to our Tobit model, we also consider the following linear regression model,

$$s_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}.$$

Since our data set is panel data, we use three panel estimation methods, pooled OLS estimation, random effect estimation, and fixed effect estimation. Each estimation method requires different assumptions about the error term. To justify the use of pooled OLS estimation, the error term should be a pure idiosyncratic shock; that is, it must satisfy the conditions that $E(e_{it}|r_{it-1,-5}) = 0$ and $E(e_{it}e_{it'}) = 0$. This is the most stringent assumption which means the error term is exogenous with respect to the regressor, and it has no serial

Figure 3: Histogram of Short Sale Ratios and 5-Day Stock Returns



correlation. However, this assumption is most likely to be violated in most time series settings.

Two panel estimation methods, namely random effect estimation and fixed effect estimation, require less stringent assumptions about the error term. Both assume that the error term consists of two components, $e_{it} = \mu_i + \varepsilon_{it}$. Random effect estimation assumes that $E(e_{it}|r_{it-1,-5}) = 0$, but fixed effect allows for $E(\mu_i|r_{it-1,-5}) \neq 0$ and requires $E(\varepsilon_{it}|r_{it-1,-5}) = 0$. Therefore, the random effect estimator is more efficient than the fixed effect estimator, but the fixed effect estimator is more robust than the random effect estimator.

As argued in Section 3, when s_{it} cannot be negative, a Tobit model is a correct method. Therefore, we estimate the following Tobit model,

$$s_{it} = \max\left(\alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}, 0\right).$$

For the estimation of the Tobit model, we also consider panel estimation techniques. Pooled Tobit estimation and random effect Tobit estimation are already well established. They are in the same principle as linear panel estimation methods, except that the normality assumption about the error term is added because the Tobit model is nonlinear; that is, pooled Tobit estimation assumes that $e_{it}|r_{it-1,-5} \sim i.i.d.\, N(0, \sigma^2)$, and random effect Tobit estimation assumes that $\varepsilon_{it}|r_{it-1,-5}, \mu_i \sim i.i.d.\, N(0, \sigma_\varepsilon^2)$ and $\mu_i|r_{it-1,-5} \sim i.i.d.\, N(0, \sigma_\mu^2)$, and they are independent each other.

However, fixed effect Tobit estimation is not available. Although following the convention of the linear fixed effect estimation, we may try to use $r_{it-1,-5} - \overline{r}_i$ as an independent variable so that each cross sectional unit has a different intercept, however we are not sure whether it is a legitimate so-called "fixed effect" Tobit estimation. Therefore, we do not consider fixed effect Tobit estimation.[6]

Estimation results of both the linear regression model and the Tobit model are presented in Table 2. One thing that we must be careful about with the Tobit model is the interpretation of coefficient of Tobit estimation results. Unlike the linear regression model, the slope

[6]Nevertheless, we estimate the Tobit model by this estimation method. Results are very similar with the pooled Tobit estimation and the random effect Tobit estimation method.

parameter, α_1, is not a marginal effect of $r_{it-1,-5}$ on $E(s_{it}|r_{it-1,-5})$. Instead, the marginal effect of the regressor on the conditional expectation of the dependent variable is given by

$$\frac{\partial E(s_{it}|r_{it-1,-5})}{\partial r_{it-1,-5}} = \Phi\left(\frac{\alpha_0 + \alpha_1 r_{it-1,-5}}{\sigma}\right)\alpha_1,$$

where $\Phi(\cdot)$ is the cdf function of the standard normal distribution. In this measure, the marginal effect of the regressor is not constant but depends on the value of the regressor. Therefore, the third column of Table 2 reports these measures that are evaluated at the average value of $r_{it-1,-5}$.

Table 2: Impact of Past Stock Returns on Short Sales

	Linear Model[1]	Tobit Model[2]	
	α_1	α_1	$\frac{\partial E(s_{it}|r_{it-1,-5})}{\partial r_{it-1,-5}}$
Pooled OLS	-0.0008	0.0196*	0.0082*
	(0.0014)	(0.0025)	–
Random Effect	-0.0009	0.0189*	0.0075*
	(0.0013)	(0.0025)	–
Fixed Effect	-0.0009	–	–
	(0.0013)	–	–

[1] $s_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}$.
[2] $s_{it} = \max(\alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}, 0)$.
[3] Numbers in parenthesis are standard errors.

Estimation results are completely different between the linear model and the Tobit model. With the linear model, coefficient estimates are all negative but are not statistically significant at any conventional level of significance. This is surprising, because our intuition is that short sellers are reacting to short-term overvaluation, but negative coefficient estimates mean that when past stock returns increase, short selling activity decreases.

On the contrary, Tobit models produce statistically significant positive coefficient estimates. Positive coefficient estimates mean that when past stock returns increase, short sale activity also increases, which is consistent with our conventional wisdom about short sellers. For the marginal impact of past stock returns on short sale ratios, we have 0.0082 and 0.0075 with pooled Tobit estimation and random effect Tobit estimation, respectively.

Meanwhile within the same model, different estimation methods do not bring significantly different estimation results. It indicates that the choice of estimation method is less important than the choice of appropriate model.

Based on these results, we may conclude that using the linear model without consideration of the non-negativity of short sales might produce erroneous coefficient estimates, and a Tobit model that can incorporate the non-negativity of short sales might be an appropriate model to analyze short sale activity.[7]

[7] In Diether et. al. (2009), they found a statistically significant positive coefficient estimate in US data (Table 3 on p. 588) with a linear regression model. However, it was done with both stock-fixed effects and both day-fixed effects. In our estimation, we do not include day-fixed effects.

To further emphasize the importance of the correct methodology to handle the non-negativity of short sales, we consider two different models where the non-negativity of short sales is not an issue: one is a time series model where all variables are aggregated over different cross-sectional units and the other is a linear model where only non-negative short sale observations are used. The time series model can be written as

$$s_t = \alpha_0 + \alpha_1 r_{t-1,-5} + e_t$$

where $s_t = \frac{1}{N}\sum_{i=1}^{N} s_{it}$ and $r_{t-1,-5} = \frac{1}{N}\sum_{i=1}^{N} r_{it-1,5}$, and the linear model with only non-negative short sale observations is in the same formula as the standard linear model,

$$s_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it},$$

however, we use only observations where $s_{it} > 0$. Estimation results are presented in Table 3.

Table 3: Impact of Past Stock Returns on Short Sales

	Time Series Model[1]	Linear Model[2] with $s_{it} > 0$
	α_1	α_1
Pooled OLS	-0.0491*	-0.0193*
	(0.0085)	(0.0026)
Random Effect	–	-0.0170*
	–	(0.0025)
Fixed Effect	–	-0.0169*
	–	(0.0025)

[1] $s_t = \alpha_0 + \alpha_1 r_{t-1,-5} + e_t$ where $s_t = \frac{1}{N}\sum_{i=1}^{N} s_{it}$ and $r_{t-1,-5} = \frac{1}{N}\sum_{i=1}^{N} r_{it-1,5}$.
[2] $s_{it} = \alpha_0 + \alpha_1 r_{it-1,-5} + e_{it}$ with observations where $s_{it} > 0$.
[3] Numbers in parenthesis are standard errors.

Estimation results are qualitatively similar with those of the linear model in Table 2. Time series models produce statistically significant negative coefficient estimates, which is difficult to reconcile with our economic intuition. Linear models with only positive short sale observations also produce statistically significant negative coefficient estimates, which is completely different from the Tobit model. The latter finding can be a textbook example of a Tobit model where if there is censoring or truncation in the data, using only uncensored or untruncated observations cannot solve the problem of inconsistent estimations.

4.3 Impact of Short Sales on Stock Returns

To investigate the impact of short sale activity on future stock returns, we consider the following two linear regression models: one without a dummy variable and the other with a dummy variable.

$$r_{it,5} = \beta_0 + \beta_1 s_{it} + u_{it}$$
$$r_{it,5} = \beta_0 + \beta_1 s_{it} + \gamma d_{it} + u_{it}$$

Since this is just a standard linear regression model, all three panel estimation methods are used for both models: pooled OLS estimation, random effect estimation, and fixed effect estimation. Their required assumptions are already mentioned in the previous subsection, so we will not repeat them here. Estimation results are presented in Table 3.

Table 4: Impact of Short Sales on Future Stock Returns

	Without Dummy[1]	With Dummy[2]	
	β_1	β_1	γ
Pooled OLS	-0.0355*	-0.0194*	0.0031*
	(0.0048)	(0.0052)	(0.0004)
Random Effect	-0.0382*	-0.0202*	0.0040*
	(0.0049)	(0.0052)	(0.0004)
Fixed Effect	-0.0400*	-0.0209*	0.0047*
	(0.0050)	(0.0053)	(0.0004)

[1] $r_{it,5} = \beta_0 + \beta_1 s_{it} + u_{it}$.

[2] $r_{it,5} = \beta_0 + \beta_1 s_{it} + \gamma d_{it} + u_{it}$ where d_{it} is a dummy variable that is set to 1 if $s_{it} > 0$ and 0 otherwise.

[3] Numbers in parenthesis are standard errors.

Estimation results are by and large in line with our conjecture that is made in Section 3. Between the different models with/without a dummy variable, the estimation results are significantly different. First, slope coefficient estimates are smaller in the model with a dummy variable than those in the model without a dummy variable. For instance, with fixed effect estimation, we have -0.0400 without a dummy, but -0.0209 with a dummy. The difference is 0.0191 which means an increase in short sales ratio by 0.01 results in a 0.191 percentage point difference in 5-day stock returns.

Second, for all three estimation methods, the dummy variable is statistically significant at the 1% level of significance. This means that the differences in slope coefficient estimates between the model without a dummy variable and the model with a dummy variable are statistically significant, which in turn implies that the model without a dummy might be a mis-specification.

However, within the same model, like the Tobit model in the previous section, different estimation methods do not bring significantly different estimates. It seems reasonable that with more than 144,000 observations, the choice of estimation methods does matter less.

5 Conclusion

We find the non-negativity of short sales can make significant differences in the estimation results. If the non-negativity is explicitly incorporated into econometric models, the impact of stock returns on short sales are completely changed. Without the consideration of the non-negativity of short sales, stock returns have either no impact or negative impact on short sale activity; however, if the non-negativity is included, stock returns have a statistically significant positive impact on short sale activity, which implies that short sellers are making their decisions based on short-term overvaluation. In the meantime, with the consideration of the non-negativity of short sales, the effect of short sales on stock returns becomes smaller, which implies that short sellers' abilities to make profits might be overevalulated in the previous literature where the non-negativity was not considered.

These findings show that the non-negativity of short sales should be considered seriously. Our findings can help not only academic researchers but also policy makers designing regulations on short selling. Correct estimates about the impact and causes of short selling are the basis of good policy response. The new econometric model in this paper can also be applied in testing the effectiveness of the regulations on short selling introduced during the global financial crisis.

In this paper, we use daily short sale and stock return data of 215 Korean firms that are listed in the Korea Composite Stock Price Index (KOSPI) from Jan. 2nd, 2006 to Sep. 30th, 2008. Although the use of this comprehensive data set is a contribution, the new econometric method should be tested using data from other countries in order to further confirm its validity. The U.S. can be the next country for this test.

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